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# Climate Conundrum: Reassessing Food Supply Resilience in South Asia

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South Asia is a populous region with high susceptibility to climate change and natural disasters which may affect the agriculture sector of these countries. Sustainable food supply is an important determinant of resilience which can be disrupted by rising temperatures and climate change. The current study is a fresh endeavor to comprehend the repercussions of climate change on food supply in case of 5 South Asiana economies. Cereal yield is used as a proxy of food supply. The study employs annual panel data spanning from 1991 to 2022. Pool Mean Group regression (PMG) is used to estimate the short run and long run coefficients. Further, fixed effect regression with Driscoll and Kraay standard errors and Dynamic Common Correlation Effects-Mean Group (DCCE-MG) is applied to ensure robust results. Findings of the study indicate that the climatic variables i.e CO2 emissions and temperature positively contribute to food supply in the long run period while both of these variables have no impact in short run. Among other variables, the cultivation area increases the food supply significantly in short run whereas use of pesticides has a positive impact in long run only. This study emphasizes the need of proactive response to deal with the possible adverse impacts of rapid climate change, even if it is not a major threat for food supply currently.
**Keywords**: Climate Change, Cereal Yield, Temperature, CO2 emissions, Agriculture, Disasters, South Asia.

## INTRODUCTION

Climate change is linked to a rapidly increasing number of natural disasters like floods, droughts and heatwaves, which is concerning for all economic sectors including the agriculture sector due to its devastating impacts. The climate induced natural disasters like droughts, heatwaves and flood can exert a shock to the agricultural output that may persist in long run (Chandio et al, 2021). According to the World Meteorological Organization (WMO), 2024 is the warmest recorded year on this planet and for the first time, the temperature crossed 1.5 °C (WMO, 2025). This realization of potentially devastating impacts of rising temperatures convinced the world nations to agree to limit the long term global average temperatures escalation less than the cap to two Celsius in light of the famous Paris Agreement (United Nations, 2025).

Agriculture sector is also directly affected by the temperature rise. The intensity of impact is often more pronounced in the less developed countries where agriculture sector constitutes a good chunk of the GDP (Warsame et al., 2021). It is also believed that CO2 emissions, in high concentrations, can provide fertilization benefits which can have a yield improvement impact (McLachlan et al., 2020). CO2 can nurture the net photosynthesis process, leading to better crop yield (Gardi et al., 2022). The positive or negative outcome is also affected by the type of crop. CO2 has potential benefits for cereals like wheat and rice, while for some other forms of cereals like millet and sorghum, higher temperatures are beneficial. Double cropping is also possible due to high temperatures. (Hannah, 2024). CO2 emissions and high temperatures. In South Asian region, a major chunk of population lives in the rural area where agriculture sector sustains an important hold in the economy as a large number of people depend on agriculture sector for livelihood. Almost, 21% population of this region faces severe food insecurity (Rehman et al., 2024).

Agricultural productivity is directly linked to the weather conditions in this region. Droughts, excessive flooding and heatwaves are major risk factors that can hamper output levels. These hazards are associated to high temperatures and exacerbated levels of emissions due to climate change (Rehman et al., 2024). Cereals like wheat, maize and rice are most consumed forms of grains around the world. Cereals are a significant source of calories consumption in South Asia, where these grains constitute almost one third portion of overall consumed level of calories (Singh et al., 2024). Therefore, cereal yield can be a good proxy of food supply.

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Sustainable food supply is often linked to the enhanced resilience levels for an economy which refers to its coping capacity in face of disruptions. A food supply shock can exacerbate vulnerability of the poor in these economies. Small farm holders are, in particular, affected by this situation. In the recent years, the countries like Pakistan, India and Bangladesh have repeatedly experienced blistering heatwaves, unpredictable rainfall resulting in flooding that threaten food security due to food supply disruptions.

Having a cursory look at the previous literature reveals that impact of climatic variables on cereal output is a well researched phenomenon in context of the time series analysis. Chandio et al. (2021) observe that, in case of Pakistan, the CO2 emissions lead to a decrease in the cereal production. This study uses the autoregressive distributed lag (ARDL) bounds tests for analysis on data for a period of 1977-2014. In another study based on the data of India for a period of 1960 to 2018, Singh et al. (2024) find that increasing the cereal crop growing area favors the cereal production, both in the short run and the long run periods. Among the climatic variables, rainfall enhances the production of cereals in short run and even in the long run periods. Among other factors, fertilizer usage turns out to have a production increasing effect. Chandio et al (2020) conducted a separate study to evaluate that how CO2 emissions, temperature and rainfall, among other variables, impacted the cereals yield. They employed data of Turkey for a time period of 1968 till 2014 to carry out the analysis. Results of their study again reflected that the climate related variables happened to affect the cereal yield in short run as well as in the long run. They also applied Granger Causality to assess the direction of relationship between the outcomes of the cereal yield and climatic variables. Temperature and rainfall turned out to have a stronger impact on cereal yield when compared to other factors like land and increased labor supply.

Warsame et al.(2021) also carried out a time series analysis in case of African country, Somalia. They used data set ranging from the year 1985 to the year 2016. Just like Chandio et al. (2020), they also applied autoregressive distributed lag (ARDL) bounds test to scrutinize the impact of the climate variables like CO2 emissions, temperature and rainfall on food supply measured through the cereal production. Granger causality was also used to examine presence of causality. Results of their study gave strong indication of a relationship in period of long run and presence of cointegration in series. They found that, in Somalia, rainfall negatively impacted the production of cereal crops but it positively enhanced it over the period of longer run. It turned out that temperature hampered the crop production in the short run period as well as in the long run. However, CO2 emissions did not have any impact neither in short run nor in long run. Land and labour supply were among the other contributing factors.

Benmehaia (2023) found in his study, based on time series data of Algeria, that the temperatures and CO2 emissions, both, exert negative impact on food supply in the long run. However, the positive rainfall shocks were linked to boosted crop levels. In another study, Chandio et al. (2025) observed that, in case of Chine, temperatures unfavorably affected the food output in both short run and long run time periods. Auto regressive distributed lag (ARDL) model was applied for analysis. Dataset ranged from 1996 upto 2019. Among other factors, R& D expenditures, internet usage and mobile phones had a positive contribution in increasing the crop yield levels. Besides the time series analysis, various studies have also attempted to explore different outcomes of the impact of climate related variables like CO2 emissions, temperatures and rainfall etc on food supply in case of panel data sets. In one such study, Bedasa et al. (2025) observed in a panel of 7 African countries, that temperatures negatively affected the cereal crop while precipitation had a positive impact. A panel Generalized Method of Moments (GMM) was used on a data spanning from 1993 to 2018. Kumar et al. (2021) found that a higher temperature had a limiting impact on food supply. On the contrary, rain and CO2 emissions boosted the production of cereals. This study was carried out on panel data of lower middle income countries for a dataset ranging from 1971 to 2016. It used Feasible east Squares (FGLS) and Fully Modified Least Squares (FMOLS) for analysis. Driscoll and Kraay regression was also applied. The study had an important policy recommendation of investing in research for developing heat resistant varieties of crops.

Abdi et al. (2023) studied the response of agricultural produce to climatic variations in the selected African nations. Results of this study revealed a positive contribution of rain and carbon emissions in cereal supply in case of long run period whereas there was a fall in supply with rise in temperature. Pooled Mean Group (PMG) technique was applied for estimation, based on data of panel of countries, included in the study from the year 1990 to 2018. Bharadwaj et al. (2022) performed a district level panel data analysis to assess the role of temperature and rainfall on two types of crops including the wheat and the rice crops. An interesting feature of their study was use of minimum and maximum temperatures for analysis. Findings revealed that while minimum temperatures enhanced the output of both crops, maximum temperature led to a fall in output. Rainfall had a limiting effect on supply of wheat.

Ul-Haq et al. (2022) documented a positive contribution of CO2 emissions and temperatures on agricultural output. Sample included data of selective South Asian nations from 1991 till 2016. The Attiaoui & Boufateh (2019) observed in their study based on 24 governorates of Tunisia from 1975 till 2014, that the prevailing temperatures are favouring the cereal production. The climate change harshly affects the cereal produce in low rainfall scenario. The estimation techniques included ARDL, PMG and Granger Causality. Appiah et al. (2018) used a panel of emerging economies with data set for time period 1971 until 2013, to analyze how agricultural

production is impacts the climate change gauged through CO2 emissions. Results indicated that agricultural production actually had a role in increasing the CO2 emissions in the selected group of countries. This study took aid of FMOLS and DOLS to draw the conclusions.

McLachlan et al. (2020) performed their analysis on a panel of 57 nations for a data set spanning from 1961 upto 2013 to analyze how crop yields were affected by the changing climate conditions and high temperature. They applied the fixed effect regression analysis to estimation. Evidence suggested that varying impact existed between impact of CO2 emissions and temperatures on food supply. Temperature negatively affected the output of wheat, maize, soybean and sorghum. For some of the crops like rice, it had an output increasing impact, but at very high temperatures, beyond 44°C, the relationship revered and temperature had adverse implications for rice yield. CO2 emissions had a positive impact on crops of wheat and rice while negative on maize, rapeseed and sorghum. Rehman et al. (2024) observed a limiting impact of climate change on food security in a panel of 5 South Asian countries. Their study employed the data for a period spanning from 1990-2021. Dynamic Common Correlation Effects (DCCE) was applied for estimation of results in this study.

Thus, the climate change variables may have implications in the short run and / or long run. This impact can be more perceptible in the long run due to gradual changes. This study endeavors to explore how climate change can potentially affect the food supply with a particular focus to selected South Asian economies. It is fresh evidence based on panel data 5 South Asian countries including Bandladesh, India, Pakistan Nepal, and Sri Lanka for 32 years spanning from 1991 to 2022. This study will be helpful to comprehend that whether climate change is really an emergency for agriculture sector in the region included in the study.

## MATERIALS AND METHODS

***Data*:** The current study undertakes the balanced panel data of 5 South Asian economies, based on data availability. These economies are Bangladesh, Pakistan, Nepal, India and Sri Lanka which are experiencing devastating impact of climate change. Further, these are highly populated nations and agriculture is one of the major sectors in these economies. The dataset ranges for a period of 1991-2022.

The econometric model in this study follows Chandio et al. (2020), Kumar et al. (2021) and Warsame et al. (2021). Data was collected from "World Development Indicators (WDI)" and Food and Agriculture Organization of the United Nations (FAO). All the variables, except for temperature, which included negative values, were transformed using the natural logarithms.

***Functional Form of Model*:** The model undertakes the following form. The cereal yield (CY) is the dependent variable while independent variable include carbon emissions (CO2), temperature (TMP), employment is agriculture (EA), use of Pesticides (PEST) and cultivation area (LYC) This model is applied to study the relationship between climate change indicators and food supply to comprehend the vulnerability or resilience of an economy against climate change.

$$YC = F(CO^2, TMP, EA, PEST, LNLYC)$$

$$LNYC_{it} = \beta_0 + \beta_1 LNCO2_{it} + \beta_2 TMP_{it} + \beta_3 LNEA_{it} + \beta_4 LNPEST_{it} + \beta_5 LNLYC_{it} + \varepsilon$$

***Estimation Techniques*:** The following estimation techniques are applied in this study. The first step is to assess basic diagnostics to comprehend the nature of data including multicollinearity, heteroscedasticity, autocorrelation and cross-sectional dependence. In the next phase of estimation, stationarity of dataset is checked and the suitable model is selected accordingly.

***Cross Sectional Dependance*:** A dependence between the countries in the data set gives rise to violation of the notion that the errors are independent across the cross sectional units. The decision about further estimation techniques rests upon the status of dependence among cross sections. Therefore, the CD test, by Pesaran (2004), is applied. The null hypotheses of absence of any dependence between the cross sections, is tested for validity against the alternative hypothesis confirming its incidence.

***Tests for Unit Root and panel Cointegration*:** The first generation unit root tests do not accommodate for cross sectional dependance. Therefore, Cross-sectional Augmented Dickey-Fuller (CADF) test and Cross-sectionally augmented Im-Pesaran-Shin (CIPS) test are used. These 2nd generation tests perform consistently in presence of country specific

**Table 1. Description of Variables.**

| Variable | Abbreviation | Units | Source |
|---|---|---|---|
| Food Supply (Cereal yield is used as proxy) | YC | Cereal yield (kg per hectare) | WDI |
| Carbon Emissions | CO2 | Carbon dioxide (CO2) emissions excluding LULUCF per capita (t CO2e/capita) | WDI |
| Temperature | TMP | Temperature change on land (°C) | FAO |
| Employment in Agriculture | EA | Employment in agriculture (% of total employment) | WDI |
| Pesticide Usage | PEST | Use per area of cropland (kg/ha) | FAO |
| Cultivation Area | LYC | Land under cereal production (hectares) | WDI |

dependence in the data set. Pesaran (2007) introduced the following statistics based on the CADF tests.

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} CADF$$

It is necessary to assess the cointegration status in presence of mixed order of integration. This study applies three tests including Westerlund, Pedroni and Kao tests to test the null hypothesis of nill cointegration. The alternative hypothesis verifies the existence of cointegration. The tests were performed after controlling for cross sectional dependence through subtraction of cross sectional means from series prior to the estimation as suggested by Levin et al. (2002).

***Pool Mean Group (PMG) Estimator*:** This study takes aid of the Pool Mean Group (PMG) estimator for estimation of short run and longer run relations. Pesaran et al. (1999) has the credit of introducing the PMG technique, that allows for heterogenous slopes in short run period. For long run period, the assumption of homogenous slopes is kept intact. Another advantage of the study is that it can be applied in case of mixed stationarity status i.e when few variables are I(0) and others I(1).

Pesaran *et al.* (1999) introduces the following model using ARDL (p, q, q…..,q):-

$$y_{it} = \sum_{j=1}^{p} \theta_{ij} y_{i,t-j} + \sum_{j=0}^{q} \phi`_{ij} x_{i,t-j} + u_i + \varepsilon_{it}$$

In the above equation, $y_{it}$ denotes the dependent variable, $x_{i,t-j}$ refers to the vector of predictors that are included in the model. Also, $\phi`_{ij}$ is the vector of coefficients. i= 1, 2, 3…, N whereas t=1, 2, 3,…., T. $u_i$ reflects the fixed effects that may fluctuate across the countries. $\varepsilon_{it}$ is the error term.

The final dynamic model for assessment of relations takes the following form:

$$\Delta y_{it} = \left(\gamma_i y_{i,t-1} + \beta`_i x_{it}\right) + \sum_{j=1}^{p-1} \theta^*_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \phi^{*`}_{ij} \Delta x_{i,t-j} + u_i + \varepsilon_{it}$$

## RESULTS AND DISCUSSION

***Results*:** The descriptive analysis and results of pairwise correlation are placed at Table 2 and Table 3, respectively. There are total 160 observations included in the panel for each variable indicating that it is a balanced panel data. Mean value of Temperature (TMP) is 0.642 Celsius with standard deviation of 0.413. The mean LNCO2 is -0.688 with a standard deviation of 0.822. Among the other variables, LNLYC has the highest mean value of 15.971.

The correlation matrix shows that LNCO2, TMP and LNPEST are positively correlated to LNYC, whereas LNEA and LNLYC are negatively correlated. Among other variables, LNEA has is having strongest correlation with LNPEST. Nevertheless, all values are < 0.8, which rules out multicollinearity in our model.

The results of CD test, placed in Table 4, exhibit strong indication of cross-sectional dependence as all variables are

**Table 2.**

| Variables | Total Obs. | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|---|
| LNYC | 160 | 7.969 | 0.260 | 7.447 | 8.518 |
| LNCO2 | 160 | -.688 | 0.822 | -2.704 | 0.654 |
| TMP | 160 | .642 | 0.413 | -0.357 | 1.615 |
| LNEA | 160 | 3.871 | 0.283 | 3.232 | 4.354 |
| LNPEST | 160 | -.911 | 1.05 | -3.507 | 0.626 |
| LNLYC | 160 | 15.971 | 1.554 | 13.455 | 18.444 |

**Table 3.**

| Variables | LNYC | LNCO2 | TMP | LNEA | LNPEST | LNLYC |
|---|---|---|---|---|---|---|
| **LNYC** | 1.000 | | | | | |
| **LNCO2** | -0.329 | 1.000 | | | | |
| | (0.0000) | | | | | |
| **TMP** | 0.502 | 0.399 | 1.000 | | | |
| | (0.0000) | (0.0000) | | | | |
| **LNEA** | -0.646 | -0.641 | -0.508 | 1.000 | | |
| | (0.0000) | (0.0000) | (0.0000) | | | |
| **LNPEST** | 0.682 | 0.536 | 0.416 | -0.740 | 1.000 | |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | | |
| **LNLYC** | -0.217 | 0.430 | -0.110 | 0.286 | -0.095 | 1.000 |
| | (0.0058) | (0.000) | (0.1653) | (0.0002) | (0.2318) | |

highly significant, failing to support the null hypotheses. Subsequently, due to presence of strong evidence favouring cross sectional dependence, CADF and modified IPS test, are applied. Result of these tests are provided in Table 4.

The null hypothesis of these tests favour non-stationarity whereas, significant results show that the data is stationary. The results of CADF test imply that in most of the cases, evidence supports the null hypothesis at level. The variables including TMP and LNLYC are significant at 1% at level showing I(0) whereas the variables LNYC, LNCO2, LNEA and LNPEST suffer from the problem of unit root. These variables become stationary at first difference showing I(1). The evidence confirms mixed stationary status for the variables included in the dataset. The outcome of mixed stationarity status is further strengthened though the results of CIPS test.

**Table 5.**

| | | |
|---|---|---|
| **Westerlund** | Variance ratio | -1.2948* |
| **Pedroni** | Modified Phillips–Perron t | -0.0059 |
| | Phillips–Perron t | -3.6684*** |
| | Augmented Dickey–Fuller t | -4.1393*** |
| **KAO** | Modified Dickey–Fuller t | -5.7880*** |
| | Dickey–Fuller t | -3.3827*** |
| | Augmented Dickey–Fuller t | -2.0520** |
| | Unadjusted modified Dickey–Fuller t | -10.0949*** |
| | Unadjusted Dickey–Fuller t | -4.2743*** |

**** p-value<.01, ** p-value<.05& * p-value<.1*

The presence of mixed stationarity order necessitates that the cointegration status of the variables must be assessed. In this study, three panel data cointegration tests including Westerlund (2005), Pedroni (1999) and Kao (1999) tests for panel cointegration are used and results are provided in Table 5. Results indicate that, except for the "Modified Phillips–Perron t" test, all of the remaining tests are significant providing strong evidence to support the notion of cointegrated series.

The short run as well as long run results are estimated through pool mean group (PMG) regression to scrutinize the influence of climate related variables like CO2 emissions and temperature alongside other control variables including the employment in agriculture, pesticide usage and cereal cultivation area on food supply. Food supply is estimated through cereal yield in South Asian region. The short run evidence indicates that only LNLYC is significant, besides constant term, at 1%, which shows that in the short run, food supply grows with increase in cultivation area. A highly significant negative 'ecm' term reflects the speed of convergence. It reflects the speed at which a short run shock will adjust to converge to the long run equilibrium.

**Table 6. PMG (Pooled Mean Group Regression)**

| | Coef. | S.E |
|---|---|---|
| **Long Run** | | |
| LNCO2 | 0.077** | (0.036) |
| TMP | 0.083** | (0.039) |
| LNEA | -0.223 | (0.144) |
| LNPEST | 0.106*** | (0.022) |
| LNLYC | 0.263 | (0.183) |
| **Short Run** | | |
| **ecm** | -0.325*** | (0.122) |
| ΔLNCO2 | 0.010 | (0.067) |
| ΔTMP | -.003 | (0.028) |
| ΔLNEA | -0.057 | (0.272) |
| ΔLNPEST | 0.050 | (0.034) |
| ΔLNLYC | 0.515*** | (0.170) |
| c | 1.668** | |
| No. of Observations | 155 | |

**** p-value<.01, ** p-value<.05& * p-value<.1; Standard errors are reflected in parenthesis.*

The long run evidence however, indicates that both of the climate related variables generate a positive influence on the food supply. Everything else being unchanged, with every one percent growth in carbon emissions (LNCO2), on average, food supply also grows by 7.7%. Likewise, every unit temperature (TMP) rise expands, on average, food supply by 8.3%, while controlling for other factors. Third factor that contributes to the food supply is use of pesticides (LNPEST) which also enhances the food supply in the long run period. Remaining two variables including cultivation area (LNLYC) and employment in agriculture (LNEA) remain insignificant but their signs are according to expectations.

***Discussion:*** The results of the study indicate strong evidence of influence of climatic variables on food supply. This influence is prevalent over the course of long run period only. In the short run, climate variables remain insignificant. Interestingly, as against the expectations, climate variables including the CO2 emissions and temperatures have augmenting impact on food supply. These results verify the previous findings of Ul-Haq et al. 2022; Abdi et al. (2023); Attiaoui and Boufateh (2019) and partially to McLachlan et al. (2020). This situation is indicating that the current levels of CO2 emissions and temperature are not directly generating any threats for the food supply chain in context of South Asian countries. There can be few possible channels through which this positive impact can be explained. The first reasons could be that the on average, the South Asian region is a warm region, temperature rise is only beneficial for the crops that require high temperatures. Second possibility indicates that the current level of technological innovations is responsible to make the crops heat resistant in the South Asian countries, where agriculture sector is one of the big sectors of economy. However, verification of these channels is left to the future research.

Findings also show that over the period of short run, food supply can simply be increased by enhancing the cultivations area. These results are in accordance with the results of Singh et al. (2024). Another finding endorses that in the long run period, use of pesticide improves the food supply. Both of these results conform to our prior expectations. Employment in agriculture sector is insignificant, in short run as well as in long run periods. Yet, sign of the coefficient meets to the theory that with more units of labour at a given land, productivity falls.

**Table 7. Panel Regression Using Driscoll-Kraay Standard Error.**

| Variables | FE | RE |
|---|---|---|
| LNCO2 | 0.103*** | -0.119** |
| | (.034) | (.052) |
| TMP | 0.080** | 0.152* |
| | (.034) | (.085) |
| LNEA | -0.513*** | -0.442*** |
| | (.071) | (.127) |
| LNPEST | 0.058*** | 0.110*** |
| | (.016) | (.014) |
| LNLYC | 0.185** | 0.025* |
| | (.086) | (.014) |
| c | 7.066*** | 9.196*** |
| No. of Observations | 160 | 160 |
| Hausman Test | $\chi^2(5)$ =126.55, p-value= 0.0000 | |

**** p-value<.01, ** p-value<.05& * p-value<.1*
*Standard errors are reflected in parenthesis.*

***Robustness:*** This study examines the robustness of the results obtained by the PMG regression through use of two distinct methods. The first one is estimation of panel regression through the Driscoll and Kraay standard errors. These are robust to the dependance across cross sections in the model. Hausman (1978) test was applied to evaluate the suitability among the fixed effect (FE) and random effect (RE) models. A significant Hausman test supports the fixed effect model. Results are provided in Table 7.

**Table 8. DCCE-MG**

| Mean Group: | Coeff | Std. Error |
|---|---|---|
| L.LNYC | -0.659*** | (0.080) |
| LNCO2 | 0.052 | (0.033) |
| TMP | 0.017 | (0.026) |
| LNEA | -0.189 | (0.128) |
| LNPEST | 0.081** | (0.041) |
| LNLYC | 0.750*** | (0.157) |
| c | -6.275** | 2.928 |
| No. of Observations | 155 | |

**** p-value<.01, ** p-value<.05& * p-value<.1; Standard errors are reflected in parenthesis.*

Further, to strengthen our confidence in results obtained through PMG, this study has applied another novel technique of Dynamic Common Correlated Effects Estimator Mean Group (DCCE-MG). The results are provided in Table 8. which are robust to our preceding findings.

***Conclusion:*** The current study underscores the significance of climatic variables in determining the food supply in a panel of 5 South Asian economies for a data that spans from 1991 till 2022. Food supply is gauged through the Cereal yield. Climate related variables include CO2 emissions and temperature. Employment in agriculture, use of pesticides and cultivation area are among the control variables. As a first step of estimation, cross sectional dependence is examined through Pesaran CD test. After, verifying the presence of cross sectional dependence, stationarity is assessed with the help of CADF and CIPS tests. Results indicate a mixed stationarity order where few variables are I(0) while others are I(1). Further, Westerlund, Pedroni and Kao tests demonstrate cointegration among the series. Finally, PMG regression is used for estimation of the coefficients during the periods of short run and longer run. A negative significant 'ecm' term, strengthens the cointegration status and shows the speed of adjustment to converge towards the long run equilibrium path.

The study demonstrates that the current levels of climate variables are not a major threat for South Asian economies included in the study. Both of the climate related variables including CO2 emissions and temperature significantly augment the food supply in the long run period. Results also suggest that, in short run, CO2 emissions and temperature have no significant impact on food supply. Further, the cultivation area enhances the food supply in short run but has no effect in the long run. Use of pesticides is though statistically insignificant in short run, it increases the food supply in long run period.

In light of the findings, this study suggests that although climate change does not seem to be a major threat currently, the governments should take proactive stance and try to invest in research for developing heat resistant varieties of crops, smart agricultural practices like tunnel farming and drip irrigation methods. Further, acknowledging the fact that this study only documents direct effects of climate change, further research is suggested to comprehend indirect channels like disasters and potential water shortage through which climate change might have potential adverse effects on agriculture sector.

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